July 2015

> Discrimination in online contracting: Evidence from Latin America

Hernan Galperin
Universidad de San Andres, Argentina
hgalperin@udesa.edu.ar

Ma. Fernanda Viecens
Universidad de San Andres, Argentina
fviecens@udesa.edu.ar

Catrihel Greppi
Universidad de La Plata, Argentina
catrihelgreppi@gmail.com

IDRC CRDI

> This work was carried out with the aid of funds allocated to the IEP by the International Development Research Centre and the Canadian International Development Agency. Ottawa, Canadá.

Hernan Galperin, M. Fernanda Viecens and Catrihel Greppi

Discrimination in online contracting: Evidence from Latin America

Lima: Diálogo Regional sobre Sociedad de la Información, (2015).

Index of Contents

Index of Tables

Index of Figures

SUMMARY

We analyze transactional data in Nubelo, a large online labor platform serving the Spanish-speaking markets. Our results indicate that employers favor domestic contractors. In our most conservative estimate, foreign workers are 15% less likely to obtain contracts in Nubelo compared to domestic workers. Yet this discrimination appears to be statistical rather than taste-based, as it decreases when more information about workers' quality becomes available to employers. Further, contrary to some of the findings in traditional labor markets, we do not find evidence of discrimination against women in online hiring. In fact, women have a small hiring advantage, particularly among female employers. However we do observe that women are less likely to submit bids and tend to ask for lower wages, particularly when bargaining with male employers. Our findings shed light on how differentials in traditional labor markets play out in online labor environments.

1. INTRODUCTION[1]

Despite overall economic growth in the past two decades, finding employment continues to be a major challenge for the millions of young Latin Americans who enter the labor market each year. This is particularly true for women. Recent data shows that about 1 in 3 women aged 18 to 24 are not in education, employment or training, compared to 13.3% for men (ECLACL/ILO, 2013). Latin American women are also less likely to enter the labor force, despite having closed the educational gap with men (IDB, 2012). More alarmingly, the rate of growth in women's labor force participation has decelerated significantly in the last decade, particularly among low-income groups (Gasparini and Marchionni, 2015).

Gender pay gaps are also persistent. This partly reflects three facts: first, Latin American women are overrepresented in low-wage occupations in the informal sector; second, they are more likely to be employed part-time; and third, they are disproportionately responsible for unpaid housework and child care (World Bank, 2012). On average, Latin American men earn 17% more than women of the same age and level of education. Interestingly, this gender pay gap tends to rise with income (IDB, 2012).

Recent studies suggest that the diffusion of new ICTs and the development of online labor markets can significantly increase employment opportunities and improve wages in emerging economies, particularly for women and youth. The argument is based on a number of stylized facts. First, the majority of employers in online labor markets are based in high-income countries, while the majority of contractors (employees) are based in middle and low-income countries (Mill, 2011). This simple fact suggests that workers may be able to earn higher (hourly) wages relative to opportunities in local labor markets. Second, many potential workers are discouraged about local job opportunities, opting out of markets with low wages or where available jobs do no match their skills. Online labor markets dramatically expand the number and range of opportunities, facilitating access to employers in global markets and increasing the likelihood that individual skills will be matched with available jobs (Lehdonvirta and Ernkvist, 2011; Agrawal et al., 2015).

Some studies indicate that the emergence of online labor is of particular value to women and the youth. For example, Rossotto et al. (2012) suggest that schedule flexibility enable online workers to balance freelance work with other responsibilities such as childcare and education. Raja et al. (2013) also suggest that, by making location irrelevant, online labor enables women to overcome some of the cultural barriers that may exist in traditional workplaces. Finally, digital labor tends to be associated with IT literacy. This naturally favors younger workers, who are more likely to have the skills and familiarity with technology required by employers.

[1] *The authors acknowledge the funding support received from the International Development Research Centre (IDRC-Canada). We are grateful to Francesc Font Cot and Nicolás Araujo Müller for granting access to Nubelo internal data. We also thank Guillermo Cruces for his valuable comments.*

However, other studies are more cautious about the development benefits of online labor. Several empirical studies indicate that workers from less-developed countries are at a disadvantage because online employers, facing limited information about job candidates, tend to favor domestic over foreign contractors, as well as contractors from more developed countries (Mill, 2011; Agrawal et al., 2013; Lehdonvirta et al., 2014). Others theorize that these platforms may exacerbate wage inequalities by further skewing work in favor of the most skilled and precluding entry by inexperienced workers (Pallais, 2014). Moreover, some note that online work may further losses in key rights associated with traditional employment such as health and pension benefits (Raja et al, 2013: OECD, 2015). Finally, facilitating part-time labor may have the undesirable effect of trapping women in lower-paying jobs (World Bank, 2012).

This paper contributes to our understanding of the dynamics and distributional effects of digital labor by exploring potential discrimination against women and workers from less-developed countries in an online labor platform serving Latin America. The study is based on the analysis of internal data from Nubelo, which to our knowledge was, at the time of writing, the largest online labor platform targeting the Spanish-speaking market. We obtained records for all transactions in Nubelo over a 31-month period between 2012 and 2014. The dataset includes basic demographic characteristics for employers and contractors (employees), and extensive platform-specific information about contracted jobs.

Our results corroborate the presence of discrimination based on worker's country of origin. In our most conservative estimate, after controlling for bid amount, job category, and a number of observable worker's characteristics, foreign workers are 15% less likely to obtain contracts in Nubelo compared to domestic workers. Yet our results also indicate that this discrimination results from lack of information about the distribution of skills among foreign workers (in other words, it is statistical rather than taste-based). By contrast, we do not find evidence of discrimination against women in online contracting. In fact, women have a small hiring advantage, particularly among female employers. However we do observe that women ask for lower wages, particularly when bargaining with male employers. We present a number of hypotheses about this gender-specific bargaining dynamics in our conclusions.

2. Online contract labor: Key characteristics

The diffusion of information and communication technologies (ICTs) is significantly changing how labor markets operate. Following Autor (2001), we identify three drivers of such change. First, search costs are significantly reduced, potentially improving matching between employers and employees. Second, increased information digitization and growing bandwidth capabilities result in more workers (particularly in the service sector) capable of performing their work remotely. Third, online delivery of labor makes location much less relevant, freeing both employers and employees from the constraints of local job markets.

We study the dynamics of a specific type of ICT-enabled labor market: online contract labor (henceforth OCL). These are digital markets in which employers offer short-term contracts for specific tasks that can be delivered remotely. OCL platforms differ from Internet job boards such as Monster.com (and its equivalent in Latin America such as Zonajobs.com and Boomerang.com) in which employers and employees seek each other to fill traditional employment positions. They are also different from online labor markets for short-term employment or tasks in which physical presence is required, such Taskrabbit.com (and its equivalent in Latin America such as Zolvers.com). Two characteristics thus define OCL platforms: a) short-term, task-based matching between freelance contractors and employers (either firms or individuals); and 2) remote labor delivery (i.e., no physical proximity between employer and contractor is required).

In general terms, OCL platforms can be divided into two types: crowdsourcing and project-based. In crowdsourcing platforms such as Mechanical Turk, large tasks are divided into smaller units and offered at a fixed price to multiple workers willing to complete them. Tasks tend to require few skills, and as a result hourly wages are generally low.[2] By contrast, in project-based platforms employers outsource larger tasks, and typically select a single contractor based on the bids received. The details of the bidding and selection mechanism vary slightly among different platforms. Most platforms are based on fixed-price bids, though some also allow for bidding based on hourly wages.

Both types of platforms have attracted significant scholarly attention in recent years. Mill (2011) analyzes internal data from Freelancer.com, a large OCL with global reach. He finds that employers favor contractors from more developed countries, but that the difference tends to disappear as personal reputation in the platform increases. Similarly, Agrawal et al. (2013) find that the benefits of verifiable work experience are disproportionately large to contractors from less-developed countries. Lehdonvirta et al. (2014) also find a significant hiring and wage penalty against foreign contractors. Stanton and Thomas (2014) explore another mechanism used by contractors to signal quality, namely, affiliation with an intermediary outsourcing agency. They find that, on average, affiliated workers obtain more contracts and better wages, but the gains tend to disappear as employers learn about individual workers' quality. Pallais (2014) shows that reputational information dramatically increases the likelihood of being hired in

[2] *Horton and Chilton (2010) found median wages in Mechanical Turk to be USD $1.38 per hour. For comparison the federal minimum wage for U.S. workers in 2010 was USD $7.25 per hour.*

OCL platforms, and is particularly valuable to entre-level workers. Horton (2013) similarly finds that algorithmically-generated recommendations reduce information frictions and improve matching between employers and employees.

3. DATA AND DESCRIPTIVE RESULTS

Nubelo is a leading OCL platform serving the Spanish-speaking market. The platform matches employers who post contracts for short-term jobs (the demand side) with contractors who bid for these jobs (the supply side). Job postings typically describe the project, the job category, the expected date of delivery, and the country location of the employer. The employer also specifies the type of bids that are accepted. While Nubelo supports both fixed-rate and hourly-rate bids, the majority of job postings (94.30%) are set to fixed-rate bidding. Employers select contractors based on the bid (price) as well as other characteristics that are visible on the contractor's online profile. A ban on employer-contractor interaction prior to the selection is strictly enforced. Therefore, all the information upon which employers select contractors is readily available in our dataset.

All potential contractors are required to complete a Nubelo profile, which contains basic characteristics such as name, country of residence, and work experience in the platform. In addition, contractors can opt to include other information such as a CV, a description about offline work experience and skills, portfolio samples, and a personal picture. After completing a project, the contractor receives feedback from the employer through a series of questions using a 5-point scale. This feedback score is also visible on the contractor's online profile.

We obtained records for all transactions in Nubelo for a 31-month period (March 2012 to September 2014). They include information on the projects posted by employers as well as on all bids placed by contractors (both winning and unsuccessful bids). Our database also includes key contractor's characteristics visible on their profiles, such as work experience within the platform, feedback scores, and country location. Gender was not included in the original dataset. We therefore assigned each contractor a gender based on the username or personal name provided in the profile. We were able to positively assign gender in 91.70% of the cases. The remainder included either ambiguous names or outsourcing agencies.

Our database is restricted to active contractors, by which we refer to those who have submitted at least one bid during the 31-month study period. Our unit of observation are the bids made by contractors. Our full dataset includes 47,469 bids made by 10,387 contractors for a total of 3,193 projects. We note appropriately when partial data subsets are used. Given that Nubelo is headquartered in Spain, prices are reported in EUR.[3]

3.1 The geography of trade

The impact of OCL platforms on the global distribution of labor is an open research question. In particular, a key question is whether employers discriminate on the basis of country location of prospective workers, and, if so, whether this discrimination is statistical (i.e., due to information uncertainty regarding worker's quality) or purely taste-based. Nubelo primarily serves the Spanish-speaking market. Therefore, while 63

[3] *At the time of writing (June 2015), 1 EUR = 1.13 USD.*

countries are represented in our database, Spain and a few large countries in Latin America account for the majority of contractors (Table 1).

Table 1. Contractors by Country of Residence

Country of residence	Total contractors	% Total contractors
Spain	4,219	40.62
Argentina	2,647	25.48
Colombia	943	9.08
Mexico	760	7.32
Chile	379	3.65
Venezuela	283	2.72
Peru	248	2.39
Uruguay	157	1.51
Ecuador	89	0.86
Guatemala	75	0.72
Others	427	4.12
Total	10,387	100

Source: Authors calculations based on Nubelo data

As expected, the distribution of employers by country is even more skewed in favor of Spain, where individuals or firms have greater incentives to seek lower-cost labor alternatives through OCL platforms. As Table 2 shows, almost two-thirds of employers reside in Spain, followed by Argentina (18.40%) and Mexico (7.10%). The share of projects posted follows a similar distribution: about two-thirds of projects originate in Spain, with the remaining third is distributed between Argentina (15.90%) and a number of other Latin American countries.

Table 2. Employers by Country of Residence

Country	Employers	% Of employers	Projects posted	% Projects posted
Spain	1,032	64.58	2,081	65.13
Argentina	294	18.40	507	15.87
Mexico	113	7.07	267	8.36
Colombia	68	4.26	113	3.54
Chile	30	1.88	82	2.57
United States	10	0.63	24	0.75
Ecuador	8	0.50	35	1.10
Others	39	2.45	84	2.68
Total	1,598	100	3,193	100

Source: Author calculations based on Nubelo data.

Descriptive results show that Spanish employers tend to favor Spanish contractors. As shown in Table 3, Spanish contractors win a larger-than-expected share of all projects, though this bias seems to be small in magnitude (about 6 p.p.), and may be related to unobserved characteristics such as higher average skills. Yet when the sample is restricted to projects originated in Spain (column c), the magnitude of the bias in favor domestic contractors becomes significantly larger (about 18 p.p. above the share of all projects). Argentine contractors are hit particularly hard, since they comprise the largest share of non-Spanish (i.e., foreign) contractors. Yet it is worth noting that due to government-set limitations to international currency trade in Argentina, Nubelo requires that Argentine employers hire Argentine contractors. This artificially inflates the percentage of all projects awarded to Argentine contractors (column b), thus also inflating their foreign penalty with respect to Spanish contractors [(c) – (b)].

Table 3. Hiring by Country location of employers and workers

Country	% Of total contractors (a)	% Projects awarded (b)	% Spanish projects awarded (c)	(b) - (a)	(c) – (b)
Spain	40.62	46.7	64.73	6.08	18.03
Argentina	25.48	31.05	15.43	5.57	-15.62
Colombia	9.08	5.07	4.23	-4.01	-0.84
Mexico	7.32	5.76	4.52	-1.56	-1.24
Chile	3.65	1.38	1.01	-2.27	-0.37
Venezuela	2.72	0.81	0.67	-1.91	-0.14
Others	11.13	9.23	9.41	-1.90	0.18
Total	100	100	100		

Source: Author calculations based on Nubelo data.

In fact, when the sample is restricted to foreign (i.e., non-Spanish) contractors, the distribution of awarded projects is proportional to the relative share of contractors by country of residence, as shown in Table 4. The exception are small countries such as Bolivia and El Salvador, in which a small number of contractors perform disproportionately well. In general, the descriptive results suggests that Spanish employers tend to favor domestic contractors, but do not discriminate within foreign contractors. This may be due to the relative homogeneity of Latin America in terms of key variables such as language, time zone, and cultural traits, which have been found to affect hiring outcomes in more globalized OCL platforms (e.g., Lehdonvirta et al., 2014).

Table 4. Non-Spanish Contractors: Hiring by Country of Residence

Country	% Of non-Spanish contractors	% Spanish projects awarded
Argentina	45.34	43.73
Colombia	12.76	11.99
Mexico	12.34	12.81
Chile	4.59	2.86
Peru	3.65	1.09
Venezuela	3.43	1.91
Uruguay	3.09	2.18
Bolivia	2.22	8.58
Cuba	2.03	2.72
El Salvador	1.39	4.63
Others	9.16	7.50
Total	100	100

Source: Author calculations based on Nubelo data.

One of the most salient questions in the literature is whether OCL platforms tend to shift the distribution of contract work from high to middle and low-income countries. In order to examine this question we look at the distribution of awarded projects using the World Bank's country wealth classification.[4] As expected, labor demand is concentrated in high-income countries, while contractors are about evenly split between high-income and upper-middle income countries (Table 5). Lower-middle income countries represent a very small fraction of both employers and contractors in our dataset.

Table 5. Employers, Contractos and Projects Awarded by Country Income Category

	% Employers	% Contractors
High-income (Spain, Chile, Uruguay, others)	67.98	53.61
Upper-middle income (Argentina, Mexico, Colombia, others)	31.32	44.39
Lower-middle income (Bolivia, El Salvador, Guatemala, others)	0.70	2.00
Total	100	100

Source: Author calculations based on Nubelo data. Most relevant countries are shown in parenthesis.

Table 6 shows trade flows between countries by level of income. The evidence indicates that two-thirds of projects originating in high-income countries are awarded to contractors in high-income countries, with only a third going to contractors in lower-income countries. This by and large reflects the fact, noted above, that Spanish employers (who represent about two-thirds of all employers) tend to contract within

[4] *The World Bank divides countries into four categories: low income (GNI per capita of $1,045 or less), lower-middle income ($1,046 to $4,125), upper-middle income ($4,126 to $12,746) and high income (over $12,746).*

Spain. Interestingly, employers in lower-middle income countries tend to hire in higher-income countries, which may reflect a scarcity of human capital available in local labor markets.

Table 6. Trade Flows by Country Income

		Contractors			
Employers	**Income Category**	High	Upper-middle	Lower-middle	Total
	High income	66.30%	28.80%	4.90%	100%
	Upper-middle income	26.70%	65.40%	7.90%	100%
	Lower-middle income	26.10%	65.20%	8.70%	100%

Notes: Excludes projects originating in Argentina because employers are required by Nubelo to hire local contractors.

Source: Author calculations based on Nubelo data.

Overall, contrary to the findings in other studies (e.g., Mill, 2011) as well as theoretical assumptions about a shifting distribution of contract labor in favor of lower-income countries (e.g., Agrawal et al., 2015), our results suggest a more limited flow of digital labor between rich and poor nations. Most projects originate in high-income countries and are awarded to local workers. More interestingly, employers in lower-income nations use OCL platforms to find talent unavailable (or priced higher) in local markets. In absolute terms, the vast majority of trade activity takes place within countries. While this may be due to the peculiarities of the platform under study (such as market segmentation by language and significant share of technical job categories), the findings suggest a more limited globalization of labor than found in previous studies.

Figure 1 maps online labor trade activity in Nubelo. Lines represent bilateral trade of services in Nubelo (i.e., hiring in both directions). Line width and color strength grow proportionally to trade volume (log scale). This graphic representation corroborates that much of the trade takes place between Spain and lower-income countries in Latin America, with only limited within-region trade.

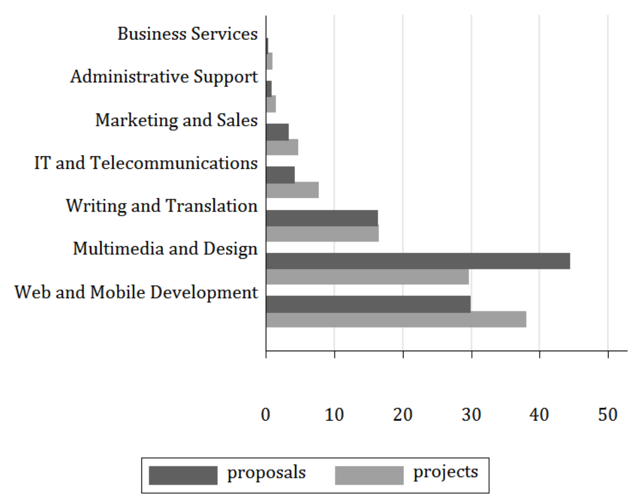
Figure 1. Trade Activity by Country

Source: Author calculations based on Nubelo data.

3.2 Prices and competition

Nubelo supports trade in a broad range of job categories. Yet as Figure 2 shows, four job categories account for the vast majority (92%) of transactions: 1) software development, 2) design and multimedia, 3) writing and translation, and 4) IT services. Demand is thus concentrated in relatively high-skill job categories, particularly when compared to labor crowdsourcing platforms such as Mechanical Turk, where lower-skills tasks (such as image identification and data entry) are most common. As expected, the market is tighter in the job categories that require more technical skills, such as software development and IT services. By contrast, competition is particularly intense for contracts in multimedia and design.

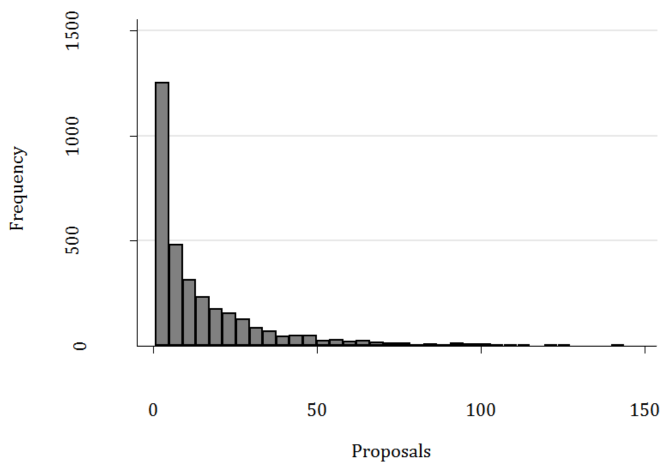
Figure 2. Projects and Bids bye Job Category



Source: Author calculations based on Nubelo data.

Differences in the intensity of competition are also observable in the average number of bids received by projects in each job category. As shown in Figure 3 most projects receive less than 50 bids, with a maximum of 144 (by definition, the minimum is 1). The mean is 14.70 bids per project (with a standard deviation of 17.90).

Figure 3. Number of Bids per Project



Source: Author calculations based on Nubelo data.

As expected, lower-skills job categories such as multimedia and design, writing and translation, and administrative support receive significantly more bids per project than higher-skills categories such as software development and IT services (Table 7). Considering the two largest job categories in terms of demand volume (which account for about two-thirds of all job postings), the average project in software development receives 64% less bids than the average project in multimedia and design. Likewise, project values vary widely by job category (Table 7). As expected, the least competitive and higher-skills job categories command the highest prices.

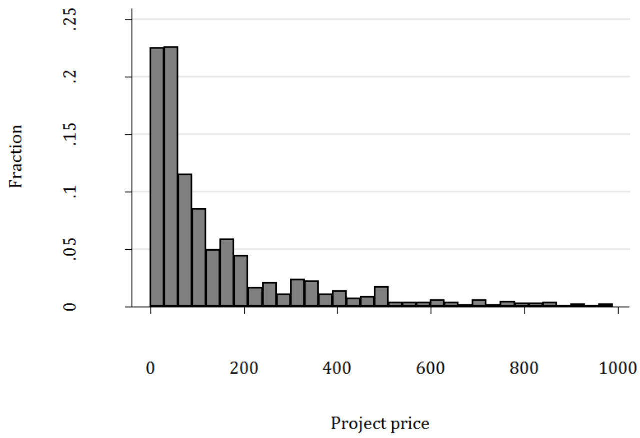
Table 7. Number of Bids Received and Average Project Price by Category

Category	Average # of bids received	Average project price (in EUR)
Multimedia and Design	44.85	$ 124.90
Writing and Translation	39.02	$ 124.70
Administrative Support	30.27	$ 300.90
Web and Mobile Development	28.61	$ 303.70
Marketing and Sales	18.00	$ 205.80
IT and Telecommunications	17.81	$ 491.80
Others	15.92	$267.30

Notes: Price calculations exclude projects nominated in Argentine pesos (posted by Argentine employers).
Source: Author calculations based on Nubelo data.

The mean price paid for a project in Nubelo is $197, but there is a large variance between projects priced at a few Euros up to large projects worth over $90,000 (the standard deviation is $692). As Figure 4 shows most projects in Nubelo are priced below $200 (the figure is truncated at $1,000 for easier visualization).

Figure 4. Distribution of Project Price (< $ 1,000.00), in EUR



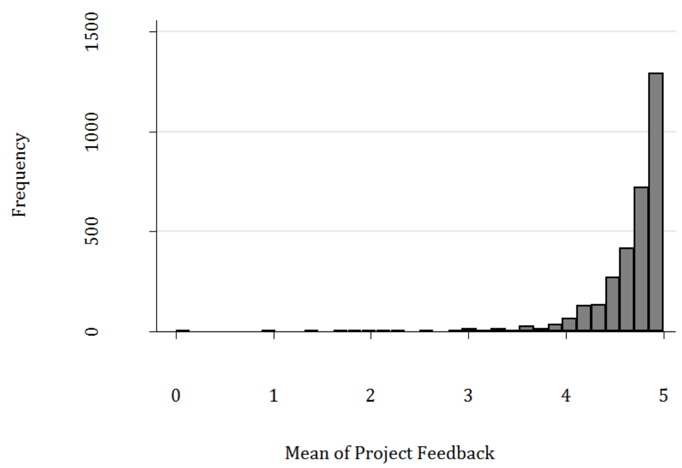
Notes: Price calculations exclude projects nominated in Argentine pesos (posted by Argentine employers).
Source: Author calculations based on Nubelo data.

3.3 Information and reputation mechanisms

Nubelo offers a number of mechanisms aimed at producing verified signals about contractor's quality. First, the average feedback score received by the contractor in previous jobs within the platform is prominently displayed in a worker's online profile. This information is nonetheless of limited value to employers for two reasons. First, because (as Figure 5 shows), the distribution of feedback scores is highly skewed towards the maximum rating of 5 (the mean is 4.7, with a standard deviation of 0.61). This lack of variance in feedback scores is in fact typical in OCL platforms.[5] Second, feedback scores are only valuable as signals for those who have already been hired in Nubelo. As discussed below, this comprises a small fraction of active contractors in the platform

[5] *For example, Pallais (2014) found that 83% of low-wage data entry workers in oDesk received a rating of at least 4, while 64% received a maximum rating of 5. Similarly, Stanton and Thomas (2014) find that about 60% of workers in oDesk received a feedback score of 5 in their first job.*

Figure 5. Distribution of Contractor's Feedback (5-point scale)



Source: Author calculations based on Nubelo data.

A second type of quality-signaling mechanisms are Nubelo-administered tests that certify specific skills (e.g., programming skills, foreign language proficiency, etc.). However, we observe that most contractors (53.50%) have never taken a test (the average number of tests taken is 1.1 with a standard deviation of 1.73). Workers can also signal stronger commitment by obtaining "premium" status in the platform, a new mechanism introduced by Nubelo in February 2014. Premium status confers two main advantages: 1) the ability to see posted projects before non-premium contractors (initially set at 24 hours, the exclusivity period was later extended to 48 hours); 2) the ability to bid for an unlimited number of projects per month (non-premium contractors are limited at 10 bids per month). In order to obtain premium status, contractors must pay a small monthly fee, currently set at $10.

As Table 8 shows, the share of premium contractors out of those submitting a bid in any given month fluctuates between 39.20% and 58.70%. Descriptive results suggest that premium status offers a considerable advantage, as premium contractors consistently obtain over 80% of the jobs posted in Nubelo.

Table 8. Premium Contractors: Share and Contracts Awarded

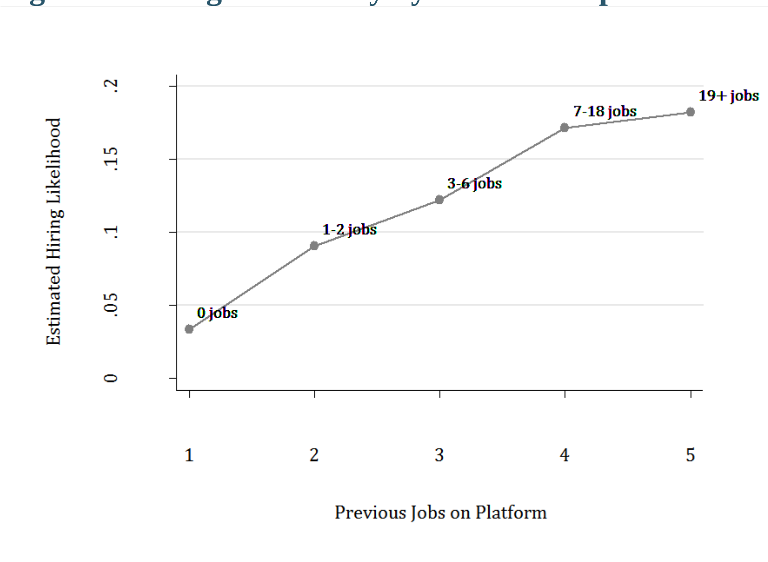
Month	% Premium contractors	% Contracts won
feb-14	58.71%	88.68
mar-14	49.07%	84.62
Apr-2014	48.75%	86.81
may-14	45.26%	85.44
jun-14	39.17%	80.75
jul-14	42.93%	86.84
Aug-2014	62.58%	92.86

Source: Author calculations based on Nubelo data.

As discussed, previous studies suggest that verifiable work experience within OCL platforms is an important determinant of the likelihood of being hired, and that this effect is larger for contractors from less-developed countries. Because employers are unable to verify job experience outside the platform (or in fact obtain any other quality signal other than what is provided in a contractor's online profile), the result is an inefficiently low level of contracts awarded to inexperienced workers (Pallais, 2014).

Our descriptive results confirms these previous findings. The likelihood of being hired increases sharply with verified platform experience, although it levels off after six jobs, indicating that, after this threshold, the marginal contribution of each additional jobs is smaller (Figure 6). Contrary to other studies, we did not find a significant difference by country of origin, which suggests that verifiable experience contributes equally to the success odds of contractors from both high and low-income countries.

Figure 6. Hiring Probability by Previous Experience in Nubelo



Source: Author calculations based on Nubelo data.

3.4 Gender differences

Nubelo is a male-dominated market (Table 9).[6] This is not surprising given that, unlike other OCL platforms, demand is concentrated in job categories more associated with men, such as software programming and IT services. More interesting is the fact that male contractors appear to be more active than female contractors, submitting a larger than expected share of bids. As shown, female contractors submitted an average of 3.70 bids during the period under study, while male contractors submitted an average of 4.60. Yet winning odds are statistically similar. Thus, male contractors win a larger than expected share of contracts simply by being more active (i.e., bidding more often) than their female counterparts.

[6] *The sample in this section is smaller because, as noted, gender could not be established for 859 contractors in our dataset (8.30% of contractors).*

Table 9. Contractors, Total Bids and Winning Bids by Gender

	Total contractors		Total bids		Winning bids		Bids per contractor	Winning odds
	Freq.	Percent	Freq.	Percent	Freq.	Percent		
Female	3,580.00	0.38	13,067.00	0.32	894.00	0.31	3.70	6.84%
Male	5,948.00	0.62	27,321.00	0.68	1,980.00	0.69	4.60	7.25%
Total	9,528.00	1.00	40,388.00	1.00	2,874.00	1.00	4.20	7.12%

Source: Author calculations based on Nubelo data.

Another indication of a gender gap in platform activity is that men are (slightly) more likely to submit the first bid to a project: while male contractors submit 68% of all bids (Table 9), they account for 74% of all first bids. This is surprising given that female contractors are more likely to have premium status than male contractors (67% vs. 61%). Recall that one the key advantages of premium status is the ability to submit bids within the first 24/48 hours after a project is posted.

One possible explanation for these findings is that women are more active in the more competitive job categories. Table 10 suggests this is the case (categories are ordered by demand volume, measured in number of projects posted). As expected, women are underrepresented in software development and IT services. These categories tend to be less competitive as indicated by the average number of bids, thus pushing up project values (Table 7 above). By contrast women are overrepresented in writing/translation and (slightly) in multimedia and design, where competition is more intense, thus driving down wages. Overall, these findings reflect traditional employment segregation patterns whereby men and women sort into different job categories.

Table 10. Gender Breakdown of Bids by Job Category

Category Name	Female	Male
Software Development	10.32%	37.18%
Multimedia and Design	45.25%	42.82%
Writing and Translation	35.72%	10.19%
IT Services	1.30%	5.70%
Marketing and Sales	4.69%	2.84%
Other categories	2.72%	1.26%
Total	100%	100%

Source: Author calculations based on Nubelo data.

Bids by female contractors are, on average, lower than bids by male contractors (Table 11). This is partly explained by the fact that women are concentrated in job categories that are more competitive, and where average project prices are lower.

Table 11. Bid Amount (in EUR) by Gender

	Mean	Median	Std. Dev.
Female	$ 283.52	$ 134.89	$ 632.91
Male	$ 339.20	$ 194.33	$ 670.27

Notes: Price calculations exclude projects nominated in Argentine pesos (posted by Argentine employers).
Source: Author calculations based on Nubelo data.

In fact, when bid amounts are broken down by gender and job category, the pattern is less clear (Table 12). While women bid lower in some of the largest job categories, they also tend to bid higher in male-dominated occupations such as IT services. We explore this question further in the next section.

Table 12. Bid Amount by Gender and Job Category (in EUR)

Category	All	Men	Women
Multimedia and Design	245.63 (2,139.74)	232.11 (1,047.49)	272.60 (3,394.46)
Web and Mobile Development	433.95 (1,427.46)	440.11 (1,534.80)	400.05 (536.50)
Writing and Translation	326.80 (2,005.22)	386.94 (3,136.92)	290.29 (698.28)
Marketing and Sales	289.35 (500.52)	293.45 (548.24)	284,27 (434.87)
IT and Telecommunications	760.65 (4,368.61)	715.74 (4,184.33)	1,013.20 (5,302.54)
Others	291.66 (411.80)	307.98 (500.01)	273,26 (281.96)

Notes: Price calculations exclude projects nominated in Argentine pesos (posted by Argentine employers). Projects that receive bids from either men or women only are also excluded. Standard deviation in parenthesis.

Source: Author calculations based on Nubelo data.

Lastly, we investigate whether gender differences in hiring are specific to the gender of the employer. Past research based on correspondence studies has found evidence of discrimination against women in male-dominated job categories and against men in female-dominated job categories (Altonji and Blank, 1999). More recently, lab and field experiments have reported similar findings (Azmat and Petrongolo, 2014; Reuben et al., 2014). However, this literature has paid less attention to gender interactions, namely, to combinations between employer (male or female) and employee (male or female).

To investigate gender interactions, we first assign gender to the employers in our dataset using a similar procedure employed for contractors. From the 47,469 observations (bids) in our original dataset, we were able to identify the gender of the employer associated with the job posting in 32,733 cases (69%). Limiting the dataset to these bids results in a smaller sample of 2,097 projects.

Interestingly, our results indicate that the overwhelming majority of employers are male (83%). When the sample is restricted to jobs posted by these male employers, we observe that male contractors win 70.90% of them. Recall that male contractors submit 68% of all bids. The descriptive analysis thus suggests the presence of a very small hiring bias in favor of male contractors among male employers, which may be due to systematic differences between male and female contractors. We resume this analysis in the next section, introducing linear models that allow for controlling for observable contractor characteristics and other covariates.

4. MODEL ESTIMATES FOR HIRING LIKELIHOOD AND BIDS

The descriptive results suggest that a number of factors are associated with employment opportunities in OCL platforms. The analysis by country indicates that domestic contractors are more likely to be hired than foreign contractors. We also observe that reputation and verifiable work experience in the platform are strongly associated with the likelihood of obtaining a contract. Most active contractors in Nubelo (i.e., those that have submitted at least one bid during the study period) have never been hired, which suggests that landing the first job is a key barrier to online employment. Lastly, the gender perspective reveals that women are less active than men in the platform, but have equal odds of being hired. Yet bids by female contractors are consistently lower, which suggests strategic behavior in anticipation of gender bias, particularly given that the majority of employers are male.

In order to test these propositions, in this section we present a series of linear probability models. First, we estimate the probability of being hired as a function of three sets of variables. The first set captures the dynamics of price competition in the platform, and includes the bid amount (i.e., the price offered by the contractor) and the number of bids received by the project (which captures the intensity of competition for the project). The second set of covariates captures the contractor's individual characteristics, including gender, profile information, work experience in the platform and country of residence. This set also includes a dummy for repeated interactions, namely, whether the employer has already hired the contractor for a previous job. The third factor captures average country reputation (as opposed to individual reputation). This is indicated by whether, at the time of bidding, the employer has ever hired another contractor from the same country of the bidding contractor.

Feedback scores are not included in the models for two reasons: first, since only a small share of contractors have work experience in the platform, most bids in our dataset were made by contractors who have never received feedback; second, because, as noted, there is very little variance in feedback scores across experienced contractors (see Figure 5). As shown in the previous section, labor supply, wages and hiring dynamics vary significantly by job category. We therefore include controls for job sectors in order to account for this source of heterogeneity.[7] Full description and summary statistics for each of the variables included in the models are presented in Appendix A. In all cases, marginal effects are interpreted at the dependent variable mean.

Results for the first set of variables are as expected: the higher the contractor's bid and the more intense the competition for the project, the lower the probability of being hired (Table 13). This result is consistent across all models presented (I-III). Next we turn to verifiable work experience in the platform. We introduce this covariate in two different ways: models I and II use a continuous variable (q) that quantifies the number of previous jobs in the platform at the time of biding, while model III uses a dummy (d)

[7] Job categories were aggregated into four sectors as follows: Sector 1 includes software development and IT services. Sector 2 includes multimedia and design services. Sector 3 includes writing and translation services. Sector 4 includes other professional services such as law, architecture, engineering, general business services and administrative support. Omitted category is Sector 1. Results do not vary when more disaggregated sectors are used.

that represents whether the contractor has any verifiable experience at the time of bidding.

As expected, verifiable experience is a strong predictor of the likelihood of being hired. Yet as discussed above (see Figure 6), the marginal contribution of each additional project tends to diminish after the first project. This is indicated in models I and II, where we observe a negative (and significant) coefficient for the quadratic term of Experience. Further, the results in model III corroborate that landing the first job is a critical barrier for obtaining contracts in OCL platforms: all else equal, having any work experience at the time of bidding increases the likelihood of being hired by about 59%.

Given the limited amount of information about contractors available to employers in the platform, even small changes in worker's online profiles have a strong effect on the likelihood of being hired. This is suggested by the size of the coefficients associated with the amount of personal information available in contractors' profiles in all models. Unfortunately, our dataset only quantifies the raw amount of information available, measured as a percentage of completed profile. Thus, beyond the general finding that more availability of personal information leads to more hiring, we are unable to determine what personal information is more valued by employers.

The results corroborate that foreign contractors face a hiring penalty. Depending on the model, foreign contractors are between 15% (model III) and 28% (model I) less likely to be hired than domestic contractors. Another important finding is that the magnitude of the penalty depends on a) whether the employer has already hired the contractor in the past (repeated interactions), and b) whether the employer has previously hired a contractor from the same country of the bidding contractor (country reputation). When these two variables are introduced, the hiring penalty for a foreign contractor drops significantly, as indicated by the magnitude of the coefficient in model I (with no controls for repeated interactions or country reputation) vs. models II and III (controlling for repeated interactions and country reputation). Calculated at the dependent variable mean, the foreign contractor penalty drops from 28% in model I to 19% in model II.

This finding is consistent with previous studies (e.g., Mill, 2011), and suggests that discrimination against foreign contractors is statistical rather than taste-based. Statistical discrimination results from imperfect information about the distribution of worker's skills (Aigner and Cain, 1977). Again, in OCL platforms employers have very limited information upon which hiring decision must be made. Lacking reliable information about worker's abilities, employers use prior beliefs about how quality is distributed among contractors based, among other things, on country of origin. Since it is likely that employers are less certain about the distribution of quality among foreign than domestic contractors, a hiring penalty results.

However, each new hiring produces new information about the quality of foreign contractors. It is also important to recall that most hiring in Nubelo results in positive matches, as evidenced by very high average feedback scores. Thus, as employers update their beliefs about the distribution of quality among foreign workers, the hiring penalty is reduced. It is interesting to note that this country reputation effect is a type of externality that affects all workers in OCL platforms regardless of their individual reputation. This is a likely explanation for why workers from different countries and in different fields tend to cluster around different OCL platforms.

Table 13. Linear Estimation of Hiring Probability

	I	II	III
a. Price competition			
Bid Amount (log)	-0.0119***	-0.0123***	-0.0123***
	(0.000998)	(0.000921)	(0.000921)
Bids Received (q)	-0.00165***	-0.00126***	-0.00125***
	(-5.17E-05)	(-4.81E-05)	(-4.81E-05)
b. Freelancer Characteristics			
Experience (q)	0.0136***	0.00758***	
	(0.000588)	(0.000548)	
Experience Squared (q)	-0.000258***	-0.000141***	
	(-1.67E-05)	(-1.55E-05)	
Experience (d)			0.0428***
			(0.00281)
% of Profile Completed (q)	0.0554***	0.0533***	0.0483***
	(0.00878)	(0.0081)	(0.00819)
Different Country as Employer (d)	-0.0206***	-0.0140***	-0.0113***
	(0.00272)	(0.00259)	(0.00259)
Previous Experience with Employer (d)		0.709***	0.715***
		(0.00973)	(0.00968)
c. Country reputation			
Previous Employer Experience with Country (d)		0.0398***	0.0397***
		(0.00348)	(0.00348)
Job Category Controls	YES	YES	YES
Constant	0.160***	0.128***	0.113***
	(0.00981)	(0.00912)	(0.00893)
Observations	34,132	34,132	34,132
R-squared	0.086	0.223	0.223
Dependent Variable Mean	0.073	0.073	0.073

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Our next set of models estimates the amount of the bid submitted by the contractor. As shown, online employers are sensitive to pricing, and therefore correctly calibrating the amount of the bid is critical for obtaining contracts. Two significant findings emerge from the results presented in Table 14. First, more experienced contractors tend to bid lower. The magnitude of this effect is very significant: on average, experienced contractors are bidding about 25% below non-experienced contractors (model III). There are several plausible explanations for this finding. The most likely is that experienced contractors also depend more on income from OCL platforms, and thus have a lower reservation price.

Second, foreign contractors tend to submit lower bids. This result may be related to several factors. On the one hand, it is possible that foreign contractors are (correctly) anticipating a hiring penalty. Further, given that most employers are located in Spain, it is likely that non-Spanish contractors from less developed countries are willing to accept lower wages. The combined effect is significant: on average, bids submitted by foreign contractors are about 13% lower, even after controlling for individual characteristics and differences related to self-selection into various job categories.

Table 14. Linear Estimation of Bid Amount (log)

	I	II	III
a. Price competition			
Bids received (q)	0.00869***	0.00884***	0.00876***
	(0.000276)	(0.000278)	(0.000279)
b. Freelancer Characteristics			
Experience (q)	-0.0383***	-0.0384***	
	(0.00318)	(0.00321)	
Experience Squared (q)	0.000601***	0.000604***	
	(9.05E-05)	(9.09E-05)	
Experience (d)			-0.246***
			(0.0165)
Different Country as Employer (d)	-0.137***	-0.115***	-0.130***
	(0.0147)	(0.0152)	(0.0152)
Previous Experience with Employer (d)		-0.0647	-0.0916
		(0.0572)	(0.0569)
% of Profile Completed (q)	-0.579***	-0.574***	-0.538***
	(0.0475)	(0.0475)	(0.0481)
c. Country reputation			
Previous Employer Experience with Country (d)		0.122***	0.122***
		(0.0204)	(0.0204)
Job Category Controls	YES	YES	YES
Constant	5.677***	5.634***	5.655***
	(0.0435)	(0.0441)	(0.0439)
Observations	34,132	34,132	34,132
R-squared	0.121	0.122	0.122
Dependent Variable Mean	336.08	336.08	336.08

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Lastly, we look at heterogeneous effects by gender. The descriptive analysis suggested that female contractors, despite having similar odds of being hired, tend to bid below male contractors. In broad terms, this result is aligned with recent studies that partly attribute the persistence of gender pay gaps to women being more risk averse (Eckel and Grossman, 2008), less competitive in labor environments (Niederle and Vesterlund, 2007), and less likely to negotiate their salary (Leibbrandt and List, forthcoming), all of which results in lower wages.[8]

To test this hypothesis, we replicate the models presented in Table 13 (hiring probability) and Table 14 (log of bid amount), adding a dummy variable for gender (female = 1). The number of observations is slightly smaller because, as noted, we were unable to establish gender for 8.30% of contractors. Given our interest in gender differences, we also drop projects that received bids from either male or female contractors only. In other words, only projects receiving bids from both male and female contractors are considered.

The results corroborate that women do not face discrimination by employers in Nubelo. In fact, after controlling for bid amount and several other individual characteristics, female contractors are slightly more likely to be hired than male contractors (model I in Table 15). On the other hand, all else equal, bids submitted by female contractors are consistently lower (model II). The magnitude of the gender difference in bids, though relatively small (about 5%), is consistent with similar findings in previous studies (e.g., Säve-Söderbergh, 2007).

Table 15. Linear Probability of Hiring and Bid Amount

	Project Accepted (I)	Log of Bid Amount (II)
Female (d)	0.0133***	-0.0471**
	(0.00283)	(0.0184)
Constant	0.0833***	5.534***
	(0.00938)	(0.0505)
Observations	26,461	26,461
R-squared	0.154	0.134
Dependent Variable Mean	0.052	4.7939
Contractor Controls	Yes	Yes
Job Category Controls	Yes	Yes

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Controls include: job category, log of bid amount (except in model II), total bids received by project, bid amount with respect to winning bid amount, work experience, previous employer experience with freelancer, if freelancer and employer are from the same country, if employer has previous experience with a freelancer from the same country, and percentage of profile completed.

Further, we break down these results by employer gender. The goal is to determine, as the literature suggests, whether gender differences in attitudes towards competition and negotiation in labor environments vary depending on the gender of the employer and the gender composition of the group against which the individual worker competes (see Gneezy et al., 2003). Recall that, while the hiring process in Nubelo does not allow for direct interactions between employers and contractors (as in traditional labor markets), contractors can typically infer the gender of the employer through either the name or the

[8] *For a full discussion see Bertrand (2011).*

picture associated with the job posting. In this analysis, we drop projects for which the gender of the employer could not be established.

The results confirm that the dynamics of hiring and competition are also specific to different employer/contractor gender combinations (Table 16). First, we note that, all else equal, female contractors are more likely to be hired by both male and female employers. However the effect is significantly stronger when the employer is also female (model III). Specifically, while female contractors are 20% more likely to be hired by a male employer, they are 39% more likely to be hired (against a male contractor) when the employer is also female.

The first effect runs contrary to common assumptions about male employers preferring male employees.[9] Our results nonetheless suggest that the second effect is significantly stronger: in Nubelo, female employers tend to hire female contractors. This finding runs contrary to the so-called "queen-bee effect" hypothesis, which posits that women that achieve higher status in male dominated job categories tend to see other women as competitors, and thus discriminate against (potential) female co-workers (e.g., Dezső et al., forthcoming).

The results for bid amounts are not entirely conclusive, but point in the direction of differentiated gender interactions. Specifically, women bid lower than men when confronted with a male employer, but their bids are statistically identical in jobs posted by female employers. A possible explanation is that they (incorrectly) anticipate discrimination by male employers, but (correctly) anticipate to be favored by female employers, thus closing the observed bid gap. This result is consistent with recent research which indicates that women ask for less but only when bargaining with men (Hernandez-Arenaz and Iriberri, 2015). Yet, more detailed research is needed to untangle the many factors affecting bargaining and bids under different gender interaction scenarios.

[9] *In reality the results from the empirical literature are inconclusive (see Blau and De Varo, 2006).*

Table 16. Linear Probability of Hiring and Bid Amount by Employer Gender

	Male Employers		Female Employers	
	Project Accepted (I)	Log of Bid Amount (II)	Project Accepted (III)	Log of Bid Amount (IV)
Female contractor (d)	0.0103***	-0.0415*	0.0194***	0.0192
	(0.0038)	(0.0242)	(0.00719)	(0.0451)
Constant	0.0931***	5.502***	0.103***	5.611***
	(0.0127)	(0.0678)	(0.0247)	(0.123)
Observations	14,987	14,987	3,575	3,575
R-squared	0.164	0.116	0.187	0.194
Mean Dependent Variable	0.0523	4.7767 (332.58)	0.0497	4.692 (239.02)
Contractor Controls	Yes	Yes	Yes	Yes
Job Category Controls	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Controls include: job category, log of bid amount (except in models II and IV), total bids received by project, bid amount with respect to winning bid amount, work experience, previous employer experience with freelancer, if freelancer and employer are from the same country, if employer has previous experience with a freelancer from the same country, and percentage of profile completed.

In our last model, we examine whether the gender of the employer affects the likelihood that a contractor will bid for that project. More specifically, we are interested in determining whether female contractors' decisions to apply for a project are affected by the gender of the employer. Modeling a contractor's decision to submit a bid (rather than the bid's amount) requires a different set of controls. In this model we control for three sets of factors. The first captures project characteristics such as amount of the winning bid (a proxy for a project's market value) and total bids received (a proxy for competition intensity). The second captures contractor's characteristics such as experience and country of residence (i.e., domestic vs. foreign contractor). We also include a dummy that captures whether the contractor has previous experience with an employer from the same country of the employer posting the job. The third set controls for variations by job category.

The results in Table 17 indicate that women are more likely to submit bids when the employer is also a women. However, the magnitude of the effect is significantly reduced as controls are introduced. Still, after controlling for project and contractor characteristics as well as job category, female contractors are about 5% more likely to submit a bid to a project posted by a female employer (calculated at the dependent variable mean). This partly explains why women are less active in Nubelo: because most employers are male, female contractors, who (correctly) believe they have a better chance of winning projects posted by female employers, tend to submit less bids than male contractors.

It is interesting to note that the coefficient for project value (i.e., winning bid) is always negative, even when controlling for job categories in model IV. This suggests that women tend to bid for lower-value projects within each of the job categories. However the magnitude of the effect is small, and may be capturing unobserved preferences for certain types of jobs or employers. Again, further research is needed to weed out alternative explanations for this finding

Table 17. Linear Probability of Bid From Female Contractor

	(I)	(II)	(III)	(IV)
Female employer (d)	0.0601***	0.0474***	0.0411***	0.0171**
	(0.00752)	(0.00773)	(0.00767)	(0.00721)
a. Project Characteristics				
Winning bid amount (log)		-0.0339***	-0.0383***	-0.00834***
		(0.00235)	(0.00234)	(0.00229)
Bids received (q)			0.00157***	0.000710***
			(0.000105)	(0.000104)
b. Freelancer Characteristics				
Experience (q)			-0.00628***	-0.00512***
			(0.000631)	(0.000594)
Different country as employer (d)			-0.0343***	-0.00468
			(0.00597)	(0.00564)
Previous experience with employer (d)			0.0952***	0.0705***
			(0.0264)	(0.0248)
c. Country Reputation			-0.0177*	0.00440
Previous contractor experience with same country (d)			(0.00998)	(0.00938)
Job Category Controls	NO	NO	NO	YES
Constant	0.309***	0.405***	0.448***	0.140***
	(0.00324)	(0.0111)	(0.0118)	(0.0128)
Observations	25,383	24,179	24,179	24,179
R-squared	0.003	0.021	0.028	0.144
Mean Dependent Variable	0.32	0.32	0.32	0.32

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

5. CONCLUSIONS

The Internet is rapidly reshaping labor markets. This study contributes to our understanding of the dynamics of hiring and resulting wages in online labor markets. While many of the conventional results in the labor literature can be replicated in digital labor environments, online hiring and remote labor delivery introduce several peculiarities that need to be established and further studied. As discussed, OCL platforms offer numerous benefits, including reduced search costs and the decoupling of labor demand and supply from geographical constraints. Yet our findings highlight numerous frictions that partly mitigate the development benefits associated with digital labor.

First, employers must make hiring decisions based on very limited information about the quality of contractors. This makes employers risk-averse, which results in a) statistical discrimination against foreign contractors (because there is likely to be more uncertainty about the distribution of quality among foreign workers), and b) high barriers to entry in OCL platforms. The first militates against workers in emerging markets, reducing opportunities to obtain higher-wage contracts from employers in more developed countries. The second is particularly unfavorable to younger workers, who are rapidly discouraged from participating in OCL platforms after failing to obtain contracts.

On the other hand, our findings suggest that OCL platforms may be of particular benefit to women, for a variety of reasons. Despite changing social norms in many emerging regions, women still bear the brunt of housework and child care. As such, labor contracts that offer flexible hours and do not require commuting are particularly suited to female workers. Our results indicate that, all else equal, women have a small but statistically significant hiring advantage over men in Nubelo, particularly when the employer is also a women. However, our results confirm that differential gender attitudes towards bargaining and competition reduce wages for women in OCL platforms. Further, we notice that this effect is particularly relevant when female contractors bargain with male employers.

A number of policy recommendations emerge from our findings. In broader terms, our results support investments in broadband infrastructure and ICT skills as a mechanism for expanding labor demand, particularly in areas where local job opportunities are limited by market size, transportation infrastructure deficits or overspecialization. Further, policy programs could encourage local firms or the government itself to hire inexperienced contractors through OCL platforms. As shown, the payoffs for landing the first job are large for individual contractors, but also help build country reputation, thus positively affecting other contractors (assuming positive feedback). Lastly, governments may provide specific training to women and young workers that focuses on reputation-building, bargaining strategies and other mechanisms associated with hiring and wage outcomes in OCL platforms.

REFERENCES

Aigner, D.J., and Cain, G.C. (1977). *Statistical Theories of Discrimination in Labor Markets. Industrial and Labor Relations Review*, 30, 175-187.

Agrawal, A., Lacetera, N. and Lyons, J. (2013). *Does Information Help or Hinder Job Applicants from Less Developed Countries in Online Markets?*, NBER WP 18720.

Agrawal, A., Horton, J. Lacetera, N. and Lyons, J. (2015). *Digitization and the contract labor market: a research agenda.* In Goldfarb, A., Greenstein, S. and Tucker, C (Eds), Economic Analysis of the Digital Economy. London: University of Chicago Press.

Altonji, J. and Blank, R. (1999). *Race and gender in the labor market*. In Ashenfelter, O., and Card, D. (Eds.), Handbook of Labor Economics, 3C, 3143–3259. Amsterdam: Elsevier.

Autor, D. (2001). *Wiring the Labor Market*, Journal of Economic Perspectives, 15, 25-40.

Azmat, G. and Petrongolo, B. (2014). *Gender and the labor market: What have we learned from field and lab experiments?*, Labour Economics, 30, 32–40.

Bertrand, M. (2011). New Perspectives on Gender, Handbook of Labor Economics, 17, 1543-1590. Amsterdam: Elsevier.

Blau, F.B. and De Varo, J. (2006). *New Evidence on Gender Difference in Promotion Rates: An Empirical Analysis of a Sample of New Hires*, NBER WP 12321.

Dezső, C.L., Ross, D.G. and Uribe, J. (forthcoming). *Is There an Implicit Quota on Women in Top Management? A Large-Sample Statistical Analysis*, Strategic Management Journal.

Eckel, C.C., and Grossman, P. J. (2008). *Differences in the economic decisions of men and women: experimental evidence.* In Plott, C. and Smith, V. (Eds.), Handbook of Experimental Economic Results, 509–519. New York: Elsevier.

International Labour Organisation (ILO) (2013). *The employment situation in Latin America and the Caribbean. Geneva:* ILO

Gasparini, L. y Marchionni, M. (2015) (Eds.). *Bridging gender gaps? The rise and deceleration of female labor force participation in Latin America.* In press, CEDLAS y IDRC.

Gneezy, U., Niederle, M. and Rustichini, A. (2003). *Performance in competitive environments: gender differences.* Quarterly Journal of Economics, 118, 1049–1074.

Hernandez-Arenaz, I. and Iriberri, N. (2015). *Women ask for less (only from men): Evidence from alternating-offer bargaining in the field*. Manuscript.

Horton, J. and Chilton, L. (2010). *The labor economics of paid crowdsourcing*. Proceedings of the 11th ACM conference on Electronic commerce, 209-218.

Horton, J. (2013). *The Effects of Subsidizing Employer Search.* Available at SSRN: http://ssrn.com/abstract=2346486.

IDB (2012). *New century, Old Disparities: Gender and Ethnic Earnings Gaps in Latin America and The Caribbean.* Washington: IADB.

Lehdonvirta, V. and Ernkvist, M. (2011). *Knowledge Map of the Virtual Economy*. Washington DC: World Bank.

Lehdonvirta, V., Barnard, H., Graham, M., and Hjorth, I. (2014). *Online labour markets – leveling the playing field for international service markets?* IPP2014: Crowdsourcing for Politics and Policy, Oxford.

Leibbrandt, A. and List, J. (forthcoming). *Do women avoid salary negotiations? Evidence from a large scale natural field experiment.* Management Science.

Mill, R. (2011). *Hiring and Learning in Online Global Labor*. NET Institute WP 11-17, Available at SSRN: http://ssrn.com/abstract=1957962.

Niederle, M. and Vesterlund, L. (2007). *Do women shy away from competition? Do men compete too much?* Journal of Economics, 122, 1067–1101.

OECD (2015). *In it together: Why less inequality benefits us all*. Paris: OECD.

Pallais, A. (2014) *Inefficient Hiring in Entry-Level Labor Markets*. American Economic Review, 104, 3565-3599.

Raja, S., Imaizumi, S., Kelly, T., and Paradi-Guilford, C. (2013). *Connecting to work. How information and communication technologies could help expand employment opportunities.* Washington DC: World Bank.

Reuben, E., Sapienza, P. and Zingales, L (2014). *How stereotypes impair women's careers in science.* PNAS, 111, 4403–4408.

Rossotto, C., Kuek, S.C. and Paradi-Guilford, C. (2012). *New frontiers and opportunities in work.* Washington D.C.: World Bank.

Säve-Söderbergh, J. (2007). *Are Women Asking for Low Wages? Gender Differences in Wage Bargaining Strategies and Ensuing Bargaining Success*. Swedish Institute for Social Research, WP Series 7/2007.

Stanton, C. and Thomas, C. (2014). *Landing the First Job: The Value of Intermediaries in Online Hiring*. Available at SSRN: http://ssrn.com/abstract=1862109.

World Bank (2012). *World development report.* Washington D.C.: World.

APPENDIX A : DESCRIPTIVE STATISTICS

Variables	Mean	Standard Deviation	Minimum	Maximum	Median
Bids Received (q)	38.49	27.84	1	144	32
Bid Amount (q)	334.81	1,918.25	0	220,000	130
Probability of Acceptance (d)	0.062	0.24	0	1	0
Experience (q)	1.77	4.92	0	57	0
Experience (d)	0.34	0.47	0	1	0
Different Country as Employer (d)	0.52	0.5	0	1	0
Previous Experience with Employer (d)	0.015	0.12	0	1	0
Profile Completeness (q)	0.82	0.16	0.2	1	0.85
Female Employer (d)	0.18	0.39	0	1	0
Female Freelancer (d)	0.32	0.47	0	1	0
Winning Bid Amount (q)	158.81	356.82	.01	27,894.99	70
Previous Freelancer Experience with Country (d)	0.15	0.35	0	1	0
Previous Employer Experience with Country (d)	0.17	0.38	0	1	0

Notes: Statistics based on sample used for OLS estimations. This sample includes only active projects and excludes employers from Argentina and projects in Argentinian pesos. Source: Author's calculations based on Nubelo data.